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A Graph-Based Feature Extraction Algorithm Towards a Robust Data Fusion Framework for Brain-Computer Interfaces

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Abstract— **Objective: The topological information hidden in the EEG spectral dynamics is often ignored in the majority of the existing brain-computer interface (BCI) systems. Moreover, a systematic multimodal fusion of EEG with other informative brain signals such as functional near-infrared spectroscopy (fNIRS) towards enhancing the performance of the BCI systems is not fully investigated. In this study, we present a robust EEG-fNIRS data fusion framework utilizing a series of graph-based EEG features to investigate their performance on a motor imaginary (MI) classification task. Method: We first extract the amplitude and phase sequences of users' multi-channel EEG signals based on the complex Morlet wavelet time-frequency maps, and then convert them into an undirected graph to extract EEG topological features. The graph-based features from EEG are then selected by a thresholding method and fused with the temporal features from fNIRS signals after each being selected by the least absolute shrinkage and selection operator (LASSO) algorithm. The fused features were then classified as MI task vs. baseline by a linear support vector machine (SVM) classifier. Results: The time-frequency graphs of EEG signals improved the MI classification accuracy by $\sim 5\%$ compared to the graphs built on the band-pass filtered temporal EEG signals. Our proposed graph-based method also showed comparable performance to the classical EEG features based on power spectral density (PSD), however with a much smaller standard deviation, showing its robustness for potential use in a practical BCI system. Our fusion analysis revealed a considerable improvement of $\sim 17\%$ as opposed to the highest average accuracy of EEG only and $\sim 3\%$ compared with the highest fNIRS only accuracy demonstrating an enhanced performance when modality fusion is used relative to single modal outcomes. Significance: Our findings indicate the potential use of the proposed data fusion framework utilizing the graph-based features in the hybrid BCI systems by making the motor imaginary inference more accurate and more robust.**

Keywords— **Brain-computer interfaces (BCI), EEG-fNIRS data fusion, Feature selection, Graph theory.**

I. INTRODUCTION

Multimodal data fusion could be very impactful yet still is under-developed for brain-computer interfaces (BCIs). Many of the existing BCI systems are based on the electroencephalography (EEG) to decode the user's neural activities noninvasively. However, often the features extracted from the EEG signals ignores the topological information hidden in the EEG spectral dynamics. Existing functional near-infrared spectroscopy (fNIRS)-based BCI systems are also challenged by the slow nature of the hemodynamic responses measured using fNIRS [1]. A few attempts have been made to integrate EEG signals with other informative brain signals such as fNIRS to develop more reliable BCI systems [2], [3], [4], [5]. New generations of the EEG-fNIRS hybrid BCIs however need to move beyond a simple concatenation of the time- or frequency-domain features through exploring novel feature extraction algorithms that puts the synergetic spatio-temporal dynamics of both modalities into perspective. Extracting complementary features is crucial to increase the performance of hybrid BCIs towards augmenting the practicality of the current systems, and will be life-changing for individuals with communication disability by providing them with effective alternative communication systems.

A. Related Work

Hybrid BCIs – In the first hybrid (EEG-fNIRS) sensorimotor rhythm (SMR)-BCIs study, conducted by Fazli et al., (2012), they found EEG and fNIRS data complement each other in terms of information content, and thus are highly suitable as a multimodal technique for hybrid BCIs [2]. Later on, Tomita et al., (2014) showed that an integrated fNIRS-EEG system could improve performance in a steady-state visual evoked potential (SSVEP)-based BCI [3]. Putze et al., (2014) showed combination of EEG and fNIRS signals can increase the discriminability of auditory and visual perceptual processes [4]. Another recent study demonstrated a significant increase in BCI performance when multimodal EEG-fNIRS recordings with deep learning was used [5].

Graph-Based Neural Features – Efforts have been made to study the topological properties of the brain in neurological disorders [6] and high cognitive functions including problem-solving and attention [7]. The graph theory approach, which is useful to illustrate a complex network architecture, has been involved in the brain function network study in the last decade. Its first application was conducted by Stam et al. [8], who compared the functional brain network of control individuals and patients with Alzheimer's disease. Many graph generation strategies has been applied. Gupta et al. [9] succeeded in using the magnitude squared coherence graph to characterize four affective states. Graph measurements such as eigenvalues has been demonstrated to be related to the graph structure and corresponding brain activities, such as seizure [10]. Most graph methods are operated in the temporal domain instead of frequency domain which usually more useful when analysing the brain connectivity.

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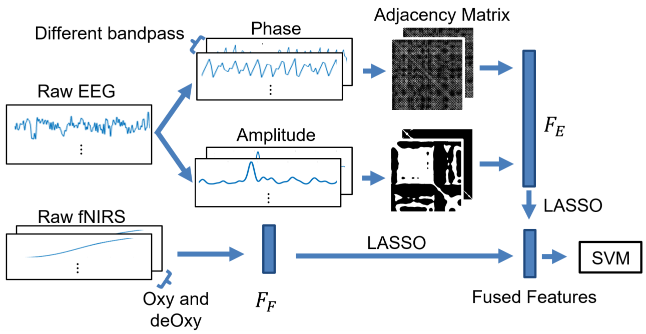

Fig. 1. An overview of the proposed method. After the raw EEG signals are bandpass filtered into Alpha and Beta bands, we calculate their instantaneous amplitude and phase sequences using complex Morlet wavelets. Adjacency matrices are then generated from the amplitude and phase sequences frame. We stack the thresholded eigenvalues from all adjacency matrices noted as F_E. The stacked fNIRS features from both Oxy and deOxy fNIRS signal frames are noted as F_F. We train a SVM binary classifier with the stacked F_E and F_F after they are LASSO selected, separately.

B. Our Contributions

In this study, we propose a novel graph-based feature extraction algorithm for a robust EEG-fNIRS data fusion framework towards developing a hybrid BCI system. An overview of our proposed method is shown in Figure. 1. The contribution of this work is three-fold: First, introducing a new prospective for graph generation in which both time-frequency component of the signal are used to build the corresponding graph. Second, extracting novel graph-based features from multi-channel EEG signals that goes beyond conventional spectral/temporal patterns and carry novel topological information of the EEG spectral dynamics. Third, the EEG-fNIRS feature fusion and feature selection to maximize the benefits of the complementary multimodal data in an effective hybrid BCIs setup. The proposed framework has been tested on the BCI dataset collected from 9 healthy subjects, in which the motor imagery (MI) experiment was performed and the EEG and fNIRS signals were collected, synchronously. We will explore whether the features extracted from the graph that is based on time-frequency maps of the EEG data have higher discrimination capability than the ones extracted from the graph directly generated from the raw temporal signals. Also, we will explore whether our multimodal feature fusion scheme enhances the performance of a motor imaginary (MI) classification task compared to when modalities are used individually.

II. METHODOLOGY

A. Data and Preprocessing

To evaluate our algorithm, we employ the motor imagery BCI datasets provided by the NeuralPC Lab at the University of Rhode Island. The experiment of the dataset is the left/right-hand motor imagery (MI) versus resting state [11] from 9 healthy participants. The EEG and fNIRS activities is recorded simultaneously using a mountage containing fNIRS optodes and EEG electrodes on a single cap. EEG data are bandpass filtered at Alpha band (8-12 Hz) and Beta band (13-25 Hz), and fNIRS data are bandpass filtered at 0.01-0.09 Hz to mitigate physiological noises caused by respiratory and cardiac activities [12]. The MI stimulation paradigm consists of three runs, each of which consists of 20 trials. Each trial performs a 10-second mental task recording and a 10-second of rest recording. During the recording, 14 fNIRS channels are monitored with a 15.6 Hz sampling rate and 13 EEG channels with a 256 Hz sampling rate. All fNIRS signals are upsampled into the same sampling rate as the EEG data.

B. Time–Frequency Processing of EEG Signals

The dynamical aspects of the EEG signals generally reveal themselves better in the frequency domain than a pure time domain analysis. Therefore, we use the complex Morlet wavelets (CMW) [13] to extract the instantaneous frequency-band–specific amplitude and phase from the multi-channel EEG signals. The time-point-wise average of the amplitude and phase series over all frequency bins (1 Hz wide) gives the frequency representation for a channel. All channels cascaded together are then considered as the time-varying amplitude series $\mathcal{A}$ and phase series $\mathcal{P}$ for the corresponding EEG signal under a given frequency band. $\mathcal{A}$ and $\mathcal{P}$ share the same dimension as the corresponding EEG signal.

C. Graph-Based Dynamical Feature Extraction

$$\mathcal{X}^{N\times d} = \begin{bmatrix} x_1^1 & \cdots & x_1^d \\ \vdots & \ddots & \vdots \\ x_N^1 & \cdots & x_N^d \end{bmatrix}$$

The recorded multi-channel raw or preprocessed EEG signals can be represented as above, where d is the number of sensor channels and N is the number of sample points in a given trial. Here, $\mathcal{X}$ can be amplitude $\mathcal{A}$, phase $\mathcal{P}$, or the raw EEG time-series. To extract a series of dynamical features from the time-varying amplitude and phase series, a spectral graph theoretical approach is applied to convert $\mathcal{X}$ into an undirected graph to decode its topological information.

Since the large number of samples (N) in a given trial would increase the computational burden of feature extraction, we generate the graph from data in a window-based manner. To do so, only the first K data point, which can be considered as a windows of K data points, in each trial are utilized. The segmented signal is denoted as $\mathcal{X}^{K\times d}$. First, pairwise similarity comparison between two rows of $\mathcal{X}^{K\times d}$, $\vec{x}_i$ and $\vec{x}_j$, is calculated as follows:

$$w_{ij} = \Omega(\vec{x}_i, \vec{x}_j) = e^{(-\frac{\|\vec{x}_i - \vec{x}_j\|^2}{2\sigma^2})},\ \forall i,j \in \{1\ldots K\}, \quad (1)$$

where Ω is a radial basis kernel function with σ^2 as the overall statistical variation between rows of matrix $\mathcal{X}^{K\times d}$. Then, a threshold function Θ is applied to convert w_{ij} into a binary form, such that $\Theta(w_{ij}) = 1$ if $w_{ij} \le r$, else $\Theta(w_{ij}) = 0$ where $r = (\sum_{i=1}^{K}\sum_{j=1}^{K} w_{ij})/K^2$.

$$\mathcal{S}^{K\times K} = \begin{bmatrix} \Theta(w_{i=1,j=1}) & \cdots & \Theta(w_{i=1,j=K}) \\ \vdots & \ddots & \vdots \\ \Theta(w_{i=K,j=1}) & \cdots & \Theta(w_{i=K,j=K}) \end{bmatrix}. \quad (2)$$

The sparse similarity matrix $S^{K\times K}$ represented in (2) is an unweighted and undirected network graph $G \equiv (V, E)$. The index of rows and columns of S represent the vertex V

of the graph G, and $w_{ij} = 1$ indicates the existence of the edge E between vertex i and j, otherwise $w_{ij} = 0$.

Once the graph G is generated, the topological information is extracted in the following process to measure the system dynamics. The degree d_i of a vertex i is calculated as the number of edges connected from i to other vertices, which is defined as: $d_i = \sum_{j=1}^{K} w_{ij}, \forall j = \{1 \dots K\}$, and the degree matrix is defined as: $D^{K \times K} \stackrel{\text{def}}{=} diag(d_1, \dots, d_K)$.

The normalized Laplacian L of the graph G is defined as:

$$L^{K \times K} \stackrel{\text{def}}{=} D^{-\frac{1}{2}} \times (D - S) \times D^{-\frac{1}{2}}, \tag{3}$$

where S is the sparse similarity matrix of graph G with all weights w_{ij}. Thereafter, the eigenvalues λ of L are computed as $Lv = \lambda v$ where v represents eigenvectors. We cascade all K eigenvalues of L into a feature vector $f^{K \times 1}$ and consider it as the dynamic feature of the signal in the corresponding window of size K samples.

In addition, we apply the same sampling window strategy on fNIRS signals $\mathcal{Y}^{N' \times d'}$ which has N' sample points and d' channels in each trial. The window size however is $K' > K$, since due to fNIRS inherent response latency and the fact that it is a signal with slower dynamics compared to the EEG. For each channel j of fNIRS, 7 features [14] are extracted from the selected window, including slop, mean, max, variance, skewness, kurtosis, and difference between the mean and the minimum. Then, we cascade these features from all d' channels to generate the feature vector ${f_F}^{7d' \times 1}$ of fNIRS signal in that given window.

D. Power Spectral Density Feature

To compare our method with the classical feature extraction approach, we calculate the signal's power spectral density (PSD) as the classical features via Welch's transform [15]. For each channel, we cascade the PSD from α and β band separately, then we squeeze those features into one vector as the PSD feature for a trial.

E. Feature Selection and Mid-Level Feature Fusion

L is symmetric positive semidefinite whose eigenvalues are nonnegative and bounded between 0 and 2. As Figure. 2 (Left) shows most of the eigenvalues are concentrated at 1 and only the ones far from 1 have separability as discriminative features. For each training fold, we only select the eigenvalues smaller than 0.9 or greater than 1.1 and keep the same eigenvalue indexes for the testing set. We cascade the thresholded eigenvalues from α and β band as F_E.

Since BCI data are usually rare and the dimension of feature vector F_E is relatively high, we apply the LASSO (least absolute shrinkage and selection operator) algorithm to perform feature selection on the F_E feature vector [16]. The LASSO selection is also applied on fNIRS features and the shrank F_F is generated. We cascade F_E and F_F and then use the fused features to perform the classification of different mental state.

The PSD features are selected using LASSO as the same as our graph features. Our proposed EEG-fNIRS data fusion framework can fuse the LASSO selected PSD feature with

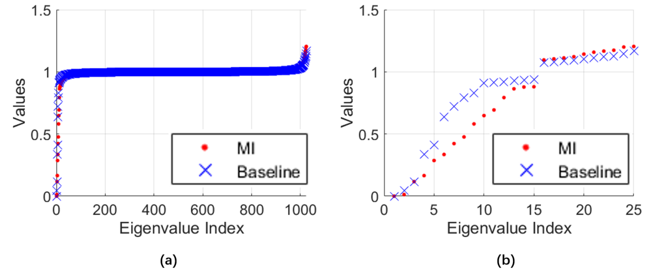

Fig. 2. Demonstration of the thresholding process to select EEG eigenvalue features and the class separability improvement based on that. (Left) The distribution of all 1024 eigenvalues generated form the 4-sec window of the MI vs. baseline trials of subject H-1. (Right) The distribution of threshold-selected eigenvalues of the same subject data.

the fNIRS feaures in the same way as the graph feature fused with the fNIRS features.

F. Inference Models

Our classification models in this study are trained and tested subject specifically assuming subject specific brain responses with 5-fold cross-validation. We employ a linear support vector machine (SVM) model as our main classifier, where its parameters including the kernel scale are automatically optimized while training.

III. RESULTS AND DISCUSSION

A. Classification details and Results

We test each subject specifically and use the first 4-second window for EEG and first 5-seconds window for fNIRS in each trial. The dimension of graph-based features are shrunk into into 7 after thresholding and LASSO for the EEG signals, same dimension for fNIRS feature by LASSO selection. The dimension for EEG-fNIRS mid-level fused feature are 14. We enumerate several choices of feature dimensions and the selected one is the best-performed set. The 1-D dimension-shrunk feature vectors from EEG signals, fNIRS signals, or the fusion of features from both modalities are then used as the input of the classifiers. Our results shows in Table. I. For EEG only case, our graph-based method and PSD both performs reach over 70% with 1.7% higher by the PSD feature. Yet the graph-based method has smaller standard deviation by 7.2%. Same situation happens in the fusion case in which the difference is 0.2%, yet the standard deviation of our graph-based method is only 8.5%, 4% smaller than the one of PSD features. Our fusion analysis revealed a considerable improvement of $\sim$ 17% as opposed to the highest average accuracy of EEG only and $\sim$ 3% compared with the highest fNIRS only accuracy demonstrating an enhanced performance in the fusion model relative to single modal outcomes.

B. Discussion

Our results show that the graphs generated using time-varying frequency-based amplitude and phase sequences separately perform better than the graph directly generated from the raw temporal EEG signals. Cascading the features from amplitude and phase graph together further improves the performance. While using the graph-based features, the

TABLE I

LINEAR SVM ACCURACY RESULTS (%) FOR EEG ONLY, FNIRS ONLY, AND EEG-FNIRS FUSION FROM 9 HEALTHY PARTICIPANTS CONDUCTING THE MI TASK. THE AP-BASED GRAPH REPRESENTS USING THE CONCATENATED EIGENVALUES FROM AMPLITUDE- AND PHASE-BASED GRAPH.

Subject Index	H-1	H-2	H-3	H-4	H-5	H-6	H-7	H-8	H-9	avg	std
Results of EEG Only											
Raw EEG-based Graph	68.9	93.3	57.8	63.3	71.1	52.5	60.0	57.1	54.0	64.2	12.6
Amplitude-based Graph	75.6	46.7	66.7	80.0	75.6	60.0	65.0	54.3	82.0	67.3	12.1
Phase-based Graph	77.8	100.0	57.8	76.7	46.7	52.5	70.0	37.1	70.0	65.4	19.0
AP-based Graph	71.1	100.0	64.4	76.7	66.7	55.0	70.0	62.9	74.0	**71.2**	**12.6**
PSD Features	82.2	100.0	75.6	93.3	62.2	57.5	35.0	77.1	82.0	**73.9**	**19.8**
Results of fNIRS Only											
fNIRS Features	93.3	100.0	100.0	83.3	68.9	100.0	65.0	91.4	94.0	88.4	13.3
Results of EEG-fNIRS Fusion											
AP-based Graph Fused with fNIRS Features	91.1	100.0	100.0	90.0	82.2	100.0	75.0	91.4	92.0	**91.3**	**8.5**
PSD Features Fused with fNIRS Features	95.6	100.0	100.0	96.7	75.6	100.0	65.0	94.3	96.0	**91.5**	**12.5**

standard deviations of accuracy are lower than using the PSD features in all cases, which indicates the graph-based feature could improve the robustness of the BCI system. The mid-level fusion of features from EEG and fNIRS improves the accuracy compared to using features from each modality, separately, which demonstrates the value of multimodal EEG+fNIRS data fusion in BCI systems. Our graph-based method reaches to very close accuracies as the PSD features in both cases, showing its potential for further improvement. Also, we consider the timepoint as the node of our graph, which causes a rather large graph and plenty eigenvalues. This inevitably introduces computational inaccuracies that could compromise the performance of the graph. Future work will address these issues for further improvement.

IV. CONCLUSION

This study focused on extracting the graph-based dynamic features from EEG signals, and evaluating its performance in an EEG-fNIRS fusion framework for classifying MI-BCI tasks. We tested our proposing graph-based EEG features both alone and fused with features form fNIRS signals using a linear SVM classifier. The framework using the graph-based on amplitude and phase features reached comparable performance to the classical PSD features, while having smaller standard deviation demonstrating the robustness of our proposed algorithm. Compared to using features from each input modality separately, the fusion strategy could considerably improve the performance of our framework. We can draw the conclusion that the proposed framework, which applies the fusion of graph-based EEG and fNIRS features, has potential value for improving the performance of hybrid BCI system with higher robustness.

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